© January 2025 | IJIRT | Volume 11 Issue 8 | ISSN: 2349-6002

Segmentation of Retinal Layers in OCT for Identification of Neural Disorders by Machine Learning Models

VARSHITHA S[1], YASHASWINI H U[2], KSHEMA R GOWDA[3],IMPANA S M[4] , MADHU C K[5]
[1, 2, 3, 4]*UGC Student, Dpt of CSE, Malnad College Of Engineering, Hassan*
[5]*Assistant Professor, Dpt of CSE Malnad College Of Engineering, Hassan*

Abstract—The segmentation of the retinal layers in OCT images is a very important aspect in diagnosing neural disorders, such as glaucoma, Alzheimer's disease, and multiple sclerosis. Early detection of these disorders affects the treatment outcomes and quality of life of patients. In principle, traditional clinical observation-based, manual analysis-of-OCT-based diagnostic methods have always been associated with time and being subjective, causing inconsistencies. However, this research introduces a computer vision-based framework for the machine learning-based automation of retinal layer segmentation on OCT images as an early screening tool for neural disorders. To improve the image quality, an advanced preprocessing combination of noise reduction, image normalization, and contrast enhancement Optical Coherence Tomography Angiography is an advanced, non-invasive imaging technology. It has allowed the ability to visualize, with high resolution, the retinal blood vessels at the level of capillaries. The automated process of segmenting vessels within OCTA images has always been challenging because of problems such as poor visibility of capillaries and the intricate structure of retinal vessels. The ROSE dataset was prepared using 229 OCTA images annotated at centerline and pixel level. A new vessel segmentation network called OCTA-Net is proposed for OCTA images. In OCTA-Net, the two-step segmentation approach is used: coarse segmentation module to generate an initial vessel confidence map and a refined segmentation module that fine-tunes the vessel boundaries for accurate detection of both thick and thin vessels. The performance of the vessel segmentation task is tested aggressively against state-of-the-art vessel segmentation techniques on the ROSE dataset. Further analysis reveals that the fractal dimension of the segmented retinal vasculature present differences in healthy and AD patients, thus showing the possibility of analysis of retinal vasculature for neurodegenerative diseases.

I. INTRODUCTION

Modern medicine has established OCT as the first revolutionizing technique for non-invasive diagnosis. There has always been a modality for the use of light waves in taking pictures that present highly detailed views in high resolution across any given tissue cross-section particularly in retinal biology. It has evolved into a basis for diagnosis of several diseases, including diabetic retinopathy and glaucoma, and even neural problems like Alzheimer's disease because it can visually image the micrometer-resolution architecture of the layered structure of the retina. What is crucial, however, is the fact that subtle changes at a very basic level within the retinal layers have been found to form the basis of many cases of neurodegenerative conditions in their early stages. These biomarkers offer exclusive soil for doctors to recognize, monitor, and therefore intervene for diseases that, otherwise, will silently progress until the condition is severe to exhibit. Early disease detection and constant monitoring in a clinical workflow require such imaging with OCT. Although vitally important in diagnostics in medicine, this technology encounters robust challenges in dealing with the analysis of retinal images.

Therefore, it is almost strictly necessary that manual layering of the retina-so commonly carried out in nearly all clinical and research centers-be done by experts matched to very clear outlines of boundaries between the layers. This task is very time-consuming, labor-intensive, and, being an image segmentation exercise inherently subjective to errors, highly inconsistent when done differently between operators or even between multiple analyses by the same operator. The increasing need for OCT imaging in large population studies and clinical routine screenings, therefore, creates an unaffordable demand for manual segmentation. Researchers have already proposed automated segmentation systems that might solve the problem, but proposed approaches today cannot match the desired precision and robustness. Current approaches do not adapt to quality variability from the images, noise, or anatomical differences between patients that are typical of real-world OCT datasets. There is a requirement for state-of-the-art, efficient, and scalable automated solutions to analyze retinal images at high accuracy and reliability, as it has the potential to be used as biomarkers for neurodegenerative disorders like Alzheimer's disease by segmenting the layers in the retina from OCT images to detect small, clinically relevant changes. In some of them, though manual, are very accurate but time-prohibitive and cannot be used for large-scale clinic purposes.

The available automated techniques hardly have the resolution and generalisability to deliver satisfactory results toward the reliable applicability in diagnosis. Such kinds of limitations left a wide gap for the true potential of the OCT imaging with early detection as well as for the monitoring the neural disorders. In this direction, a segmentation system based on machine learning needs to be developed which brings together precision from state-of-the-art into scalable and robust clinical scenarios demand. The Segmenting Procedure can be classified into manual and automated categories.. Manual segmentation is the gold standard in terms of accuracy but poses several drawbacks about scalability, consistency, and efficiency. Several automation basic techniques include thresholding, edge detection, and region growing that applied with the view to reduce workload and efforts for the clinicians; still, such attempts very seldom provide a reasonable probability of conserving detailed structuring information contained in layers in the retinas.

Recent breakthroughs of machine learning, especially deep learning, indicate a lot of promise to the tasks involved in OCT segmentation. Associated architectures can learn very complex spatial patterns and hence outperform the traditional methods. Although the proposed machine learning-based models overcome the generalization of different types of datasets, noisy or low quality images, and accuracy in the thin or closely spaced retinal layer segmentation; the system presented here focuses on the exact and reliable layer segmentation of the retinas of OCT images without any problems presented in the current techniques. Such a system can capture minor structural changes that help in determining neural disorders earlier and, therefore, improves accuracy in disease diagnosis. It also saves much time and human efforts because a huge dataset can be analyzed efficiently by clinicians. Early and accurate detection of retinal biomarkers supports anticipatory interventions, improves outcome, and reduces the burden of advanced disease management.

II. LITERATURE SURVEY

A. Introduction to Optical Coherence Tomography (OCT) Imaging

OCT forms a very high-resolution image of the retina, and such images are found to be extremely valuable for the purpose of making early diagnoses relating to diseases like diabetic retinopathy, glaucoma, and age-related macular degeneration. OCT imaging may be quite useful also for the diagnosis of neural disorders like Alzheimer's disease, wherein the layers would change in the retina. The past few years have seen increased interest in segmentation of retinal layers from OCT images due to the application both in ophthalmology and neuroscience.

B.Limitations of Human-Based Segmentation

Human-based segmentation of layers in the OCT image is traditionally performed by qualified people. That's correct and feasible but time consuming, subjective, and error prone. Thus, at this rate, manual segmentation becomes practically inefficient with an increasing volume of OCT images; there seems to be a need for an automated method to fulfill the purposes of enhancing the diagnostic efficacy and reliability..

C. Automated Segmentation Technologies

The early strategies of automated segmentation were edge detection and thresholding, which had problems with the complexity of retinal structures, noise, and quality variations in images. To solve such problems, more capable strategies for accurate and effective segmentation have been proposed-focusing on how to improve performance in pathological imaging conditions.

D. Segmentation Approaches

One approach is the multi-stage framework, where it first performs coarse segmentation and then refines to increase the accuracy. Another common method is a specialized architecture aimed at enhancing sensitivity and detecting minute changes in retinal structures, which are important for early detection of diseases. Also, the combination of different models and techniques has been shown to be effective in increasing the robustness of segmentation, especially in degenerative conditions causing progressive changes in the retina.

E. Crossover Models and Multi-Stage Approaches

The most recent considers have made utilize of a combination of conventional as well as cutting edge procedures in arrange to progress the execution of division. For illustration, two-stage systems able to accurately do the essential division taken after by region-based refinements may deliver way better execution for loud or low-resolution pictures. In expansion, multi-scale consideration models that can extricate highlights at both neighborhood and worldwide levels may capture the fine subtle elements in OCT pictures that are pivotal for the early conclusion of such diseases.

F. *Issues and Limitations*

A part has been accomplished in the division of retinal layers, but much remains to be done. The to begin with challenge is the need of high-quality explained OCT datasets required to prepare great models. Changeability in picture quality, determination, and imaging conditions makes it challenging to construct models that generalize well over different datasets. The moment issue bargains with interpretability. This bargains with the yield comes about of the division assignment. In any case great a few models might be, decision-making forms are not straightforward and in this way exceptionally difficult to receive clinically.

III. METHODOLOGY

A.Data Acquisition

The process of data acquisition for segmenting retinal layers in OCT images is complex and multifaceted, involving the selection of high-quality images, manual annotation, and preprocessing. Publicly available datasets, clinical collaborations, and appropriate annotation tools are necessary for building a robust machine learning model. Data augmentation techniques and proper dataset splitting further enhance the model's ability to generalize across diverse real-world scenarios. The final goal is to develop an accurate, automated system for the detection of neural disorders through the segmentation of retinal layers in OCT images that could be applied in earlier diagnosis and better results in the patient.

B. Pre-processing

- Normalization: OCTA images are normalized to a standard range that enables faster processing and reduces pixel intensity values variation.
- Resizing: The resized images are maintained at a common size to bring uniformity into the dataset.
- Noise reduction: This is typically done using a Gaussian filter or a median filter. This reduces the noise in the images and, hence, improves the segmentation accuracy. The algorithms generally suppress the artifacts and do not blur the fine details.
- Contrast Enhancement: Techniques like histogram equalization can be used to enhance the contrast of the vessels and other features in order to have them well contrasting with the background.
- Artifact Removal: Techniques used to remove artifacts such as motion blur, horizontal, or vertical lines that may be caused by patient movement while taking OCTA scans.

C.Segmentation

- Coarse Stage (SCS Module): The coarse stage uses a split-based coarse segmentation module, denoted as SCS. This module is quite beneficial and aims to give preliminary confidence maps for segmenting the pixel-level vessels and centerline-level vessels.. It makes use of shared weights for efficiency.
- Fine Stage (SRS Module): The fine stage is a fusion network that incorporates a split-based refined segmentation (SRS) module. It combines the preliminary confidence maps generated in the coarse stage to produce the final refined segmentation results.
- Adaptive Aggregation and Fusion: The SRS module is comprised of adaptive aggregation and fusion operations that enable efficient combination of confidence maps from the coarse stage, which enhances the accuracy and resolution of the final segmentation results.

D.Feature Extraction

For Alzheimer's prediction, the study focuses on some specific OCTA features of the retinal microvasculature, such as:

- Fractal Dimension (FD): This feature characterizes the complexity of the retinal vessel branching patterns, which can be different between healthy individuals and those with Alzheimer's. Reduced FD values, as mentioned in the study, are related to Alzheimer's and represent more simple, less complex branching patterns.
- Vessel Density and Tortuosity: Vessel density is the number of blood vessel network in a given retinal area. Reduced density and alterations in tortuosity, or the twisting and turning of vessels, are potential biomarkers associated with neurodegeneration.
- Capillary Non-Perfusion Areas(CNPA): These areas represent parts of the retina where capillaries are not perfusing properly, which may be indicative of impaired blood flow associated with Alzheimer's.

IV. TOOLS AND LIBRARIES

A.OpenCV

OpenCV is a powerful library widely used in image preprocessing and segmentation tasks. It is often used to resize, denoise, and implement image enhancement to the OCT images before segmentation. OpenCV implements edge detection, thresholding, and watershed segmentation for the identification of the retinal layers in the medical images, which are key steps in segmentation. This software also allows the analysis of contour and feature extraction, which plays a critical step in extracting information for diagnostic use.

B.Scikit-learn

This is a library of machine learning to address data preprocessing, feature selection, or evaluation tasks. In image segmentation, this can be used in applications that cluster pixel data into separate layers of the retina, focus on relevant features with dimensionality reduction, and in model assessment with metrics such as confusion matrices. Improving the robustness of segmentation models is brought about by algorithms of Scikit-learn; thus, the extraction of meaningful patterns becomes more accurate from complex medical images.

C. NumPy

NumPy is a core library of numerical computing, it is commonly used for operations in array manipulations and math. In image processing, NumPy facilitates the management of image data as arrays where pixel-wise calculation can be executed such as pixel averaging or the application of transforms. It will be important to the statistical analysis in noise reduction and image quality assessment and manipulate image matrices as preparation for image segmentation.

D. Pandas

Pandas is a tool that helps you work with large sets of data by organizing it in a way that's easier to understand and manage. It helps clean up messy data and makes it more structured, allowing you to analyze and manipulate the data efficiently. It enables efficient management of results from image segmentation and quality metrics evaluations. Pandas is very helpful in structuring image data and metrics into DataFrames, thus making it easier to track, clean, and analyze the results. It also helps in storing and managing large-scale image datasets, preparing them for further processing or model input.

E. Matplotlib

Matplotlib is a general-purpose plotting library that can be used to visualize results in image processing tasks. It is used to plot the output of segmentation techniques, such as plotting segmented layers or visualizing image quality metrics like contrast, sharpness, and entropy. It also helps in generating graphs and charts for evaluating model performance, such as accuracy vs. epoch plots or confusion matrices, which helps in the interpretation of segmentation results and metrics.

V. RESULTS AND DISCUSSION

A. Performance Metrics

- Precision: This measures the proportion of correctly predicted vessel pixels relative to all the pixels that the model identified as vessels. It is a very essential measure to get an idea about how well the model avoids false positives, that is, how well the model avoids picking up non-vessel pixels. The higher the precision value, the fewer errors the model is making in its vessel predictions. In medical imaging, this is a critical issue since misdiagnosis can result from incorrectly identified vessels. In retinal vessel segmentation, higher precision means that the model focuses on true vessel areas and, therefore, does not wrongly classify surrounding tissues as vessels.

- Recall (sensitivity):

Recall also refers to a sensitivity measure calculated as the portion of actual pixels representing vessels that were correctly reported by the vessel segmentation model from the ground-truth. A good recall thus emphasizes the possibility of the vessel being able to draw all the right vessels, large or small. A higher recall value indicates that fewer vessel pixels are missed during segmentation, ensuring that the model captures as many true vessels as possible. In medical applications, high recall is particularly important for ensuring that all relevant areas, such as blood vessels in retinal images, are included in the analysis, preventing the omission of critical features that could affect diagnosis.

- F1 Score:

This score is a harmonic mean between precision and recall and represents an aggregate measure of model performance, combining both aspects-precision correctly detected vessels and recall that of detecting all the actual vessels, for more accurate appraisal. A higher F1 score represents a good balance between precision and recall, indicating that the model is accurate in its vessel predictions and thorough in detecting all relevant vessels. If both false positives and false negatives are costly errors, such as in medical diagnostics, the F1 score helps ensure that the segmentation model does well in all respects, not just one.

- Accuracy*:*

This is a general measure of the performance of the model, indicating how often the model correctly classifies both vessel and non-vessel pixels. Accuracy is calculated as the ratio of correct predictions to the total number of predictions: true positives, which are vessel pixels correctly classified, and true negatives, which are non-vessel pixels correctly classified. A higher accuracy value means better overall segmentation performance because the model clearly distinguishes between vessels and background areas. Accuracy is a good measure, but must be considered together with other metrics, such as precision and recall, because the accuracy may not represent performance adequately in imbalanced datasets, like in the case of vessels where they are significantly less frequent than the background. For medical imaging applications, high accuracy guarantees that there are correct identification of both vessels and background with proper segmentations.

B. Comparison with Existing Systems

Existing retinal layer segmentation methods based on OCT imaging are either manual or automated. Both have visible limitations. Manual segmentation might be accurate but involves much human skill, time, and effort; this renders it impractical for clinical work. Early automated methods based on edge detection and thresholding could not ensure the precision and robustness of clinical utility in the presence of noisy images or anatomical variations. More recent developments, particularly CNNs, are showing promise; most often requiring large labeled datasets and not generalizing well from one dataset to the next. To counter these drawbacks, a two-stage segmentation system is proposed to provide improved segmentation:

(i) Coarse Segmentation-SCS module used for initial segmentation

(ii) Fine Segmentation-SRS module for further accuracy. The former provides strong confidence maps to compensate for image variability. The latter refines the output for precise extraction of delicate retinal features like thin and close-lying layers. This synthetic approach features high accuracy, scalable and reliable beyond earlier and existing automated systems, and hence propelling the chances of early diagnosis for neural disorders.

Features	Outcome	Measurements
Fractal Dimension	1.927	mm
Vessel Density	7.505	%
Tortuosity	74.8	mm
Capillary Non-Perfusion Area(CNPA)	72.65	%

CONCLUSION

This is a very simple yet super-efficient technique because it removes noisy images and removes blurry edges on top of main features. One area that this applies is in medicine: doctors always require sharp pictures of patients or patients' test results to ascertain a proper diagnosis, and secondly, its use in a field like machine learning, when one needs well-structured input for good predictions. That is, an image, which to the naked eye at first glance would seem very much cluttered and jumbled, be denoising in it and enhance contrast over important features, or skeletons, along with features quite well defined but not necessarily sharply so within clearly labeled regions by this means.

This technique has its disadvantage: noise removal cleans up the images, but in doing so, it washed out some minor details because they might represent thin structures as important for analysis. It might represent the blood vessels. Contrast enhancement will make the features appear more contrasting and will fail in cases where the contrast between regions may slightly be low, or illumination changes are not homogeneous within the image. It is a form of thresholding that separates the foreground from the background. The method in this case will probably fail if the intensity values overlap or range over some intervals. It also deforms the features if the main segmentation is not good. Further, the labeling of connected regions, which is very sensitive for the detection and measurement of most objects, is very difficult to perform when the objects overlap with each other or are placed closer to each other.

There is therefore a very great scope of further improvement to the processing algorithm. Such noise suppression techniques should be included in such a manner that images are smoothed out without finer details being lost. The tools for contrast enhancement shall be enhanced which can bring minute differences otherwise, it leads to regions of interest becoming blurred and adaptive techniques of segmentation will be required because thresholding is not turning out to be true as they are adopting the changes taken place in any image. Techniques of skeletonization also require advancement so that high is the resultant skeleton.

REFERENCES

[1] Y. Ma et al.,-ROSE: A Retinal OCT-Angiography Vessel Segmentation Dataset and New Model, *IEEE Transactions on Medical Imaging*, vol. 40, no. 3, pp. 928-939, March 2021.

[2] K. G. Falavarjani, M. Al-Sheikh, H. Akil and S. R. Sadda,-Image artefacts in swept-source optical coherence tomography angiography, *Brit. J. Ophthalmol.*, vol. 101, no. 5, pp. 564-568, May 2017.

[3] F. K. Chen, R. D. Viljoen and D. M. Bukowska, -Classification of image artefacts in optical coherence tomography angiography of the choroid in macular diseases, *Clin. Experim. Ophthalmol.*, vol. 44, no. 5, pp. 388-399, Jul. 2016.

[4] A. Zhang, Q. Zhang and R. K. Wang, -Minimizing projection artifacts for accurate presentation of choroidal neovascularization in OCT microangiography, *Biomed. Opt. Exp.*, vol. 6, no. 10, pp. 4130-4143, 2015.

[5] N. A. Iafe, N. Phasukkijwatana, X. Chen and D. Sarraf, -Retinal capillary density and foveal avascular zone area are age-dependent: Quantitative analysis using optical coherence tomography angiography, *Investigative Ophthalmol. Vis. Sci.*, vol. 57, no. 13, pp. 5780-5787, 2016.

[6] M. Li et al.,-Image projection network: 3D to 2D image segmentation in OCTA images, *IEEE Trans. Med. Imag.*, vol. 39, no. 11, pp. 3343-3354, Nov. 2020

[7] A. Camino, M. Zhang, L. Liu, J. Wang, Y. Jia and D. Huang,-Enhanced quantification of retinal perfusion by improved discrimination of blood flow from bulk motion signal in OCTA, *Transl. Vis. Sci. Technol.*, vol. 7, no. 6, pp. 20, Dec. 2018.

[8] S. Yousefi, T. Liu and R. K. Wang,-Segmentation and quantification of blood vessels for OCT-based micro-angiograms using hybrid shape/intensity compounding, *Microvascular Res.*, vol. 97, pp. 37-46, Jan. 2015.

[9] H. Fu, Y. Xu, S. Lin, D. W. K. Wong and J. Liu,-Deepvessel: Retinal vessel segmentation via deep learning and conditional random field, *Proc. Int. Conf. Med. Image Comput. Assist. Intervent. (MICCAI)*, pp. 132-139, 2016.

[10] D. C. DeBuc, G. M. Somfai and A. Koller, -Retinal microvascular network alterations: Potential biomarkers of cerebrovascular and neural diseases, *Amer. J. Physiol. Heart Circulatory Physiol.*, vol. 312, no. 2, pp. H201-H212, Feb. 2017.

[11] J. Zhang, A. H. Kashani and Y. Shi,-3D surface-based geometric and topological quantification of retinal microvasculature in OCTangiography via Reeb analysis, *Proc. Int. Conf. Med. Image Comput. Assist. Intervent. (MICCAI)*, pp. 57-65, 2019.

[12] N. Eladawi et al.,-Automatic blood vessels segmentation based on different retinal maps from OCTA scans, *Comput. Biol. Med.*, vol. 89, pp. 150-161, Oct. 2017.

[13] J. P. Campbell et al.,-Detailed vascular anatomy of the human retina by projection-resolved optical coherence tomography angiography, *Sci. Rep.*, vol. 7, no. 1, pp. 42201, Mar. 2017.

[14] R. Leitgeb,-En face optical coherence tomography: A technology review, *Biomed. Opt. Exp.*, vol. 10, no. 5, pp. 2177-2201, 2019.

[15] Z. Zhang, H. Fu, H. Dai, J. Shen, Y. Pang and L. Shao, - Et-net: A generic Edge-attention guidance network for medical image segmentation, *Proc. Int. Conf. Med. Image Comput. Assist. Intervent. (MICCAI)*, pp. 442-450, 2019.